Evaluation of Uncertainties of Predicted System Attributes

Presented at

Advanced Simulation:

A Critical Tool for Future Nuclear Fuel Cycles Workshop

Paul Turinsky

Academic Center of Excellence

In

Advanced Modeling and Simulation

North Carolina State University

Goal of Uncertainty Analysis

- Determination of the uncertainties [and sensitivities] in predictions of key performance attributes associated with the fuel cycle due to input data and modeling uncertainties.

- Includes for example such key performance attributes of
  - nuclear power plants (thermal margins, reactivity coefficients, SDM)
  - repository performance (heat loads, radio-toxicity)
  - fuel cycle proliferation resistance (SNM inventories)

Usages of Uncertainty Analysis

- Define system design margins required.
- Alter system designs to make less sensitive to input data uncertainties.
- Determine where costs of additional experiments and/or modeling improvements are justified by savings in using reduced design margins.

Possible Uncertainty & Sensitivity Analyses Approaches

- Standard Forward Approach
  - Randomly perturb input data based upon their known or assumed probability distributions.
  - Attributes
    - Simple to implement for uncorrelated input data
    - Well suited for problems with many key attributes and limited input data
    - Provides probability distributions of key attributes
    - Difficult to obtain sensitivity coefficients from
    - Correlated input data present several challenges

Possible Uncertainty & Sensitivity Analyses Approaches

- Standard Inverse Approach
  - [Generalize Perturbation Theory]
- Attributes
  - More difficult to implement with significant development effort, particularly for linked modules sequence
  - Well suited for problems with many input data and few key attributes
  - Does not provide probability distributions of key attributes
  - Directly obtain sensitivity coefficients
  - Correlated input data treated without difficulty

Possible Uncertainty & Sensitivity Analyses Approaches

- **Modified Forward Approach**

1. Determine Singular Value Decomposition (SVD) of covariance matrix associated with input data using Efficient Subspace Method [ESM*], which involves covariance matrix operating on random vectors to determine the subspace rank "r" bases vectors.
2. Utilizing the "r" bases vectors for the subspace as identified by SVD as input data to system model, execute the system model a total of "r" times.
3. Complete a SVD of system model response matrix to determine covariance matrix of key attributes of system.

- Note that Step 1 when applied to the system model generates the SVD and hence subspace associated with the Jacobian matrix.

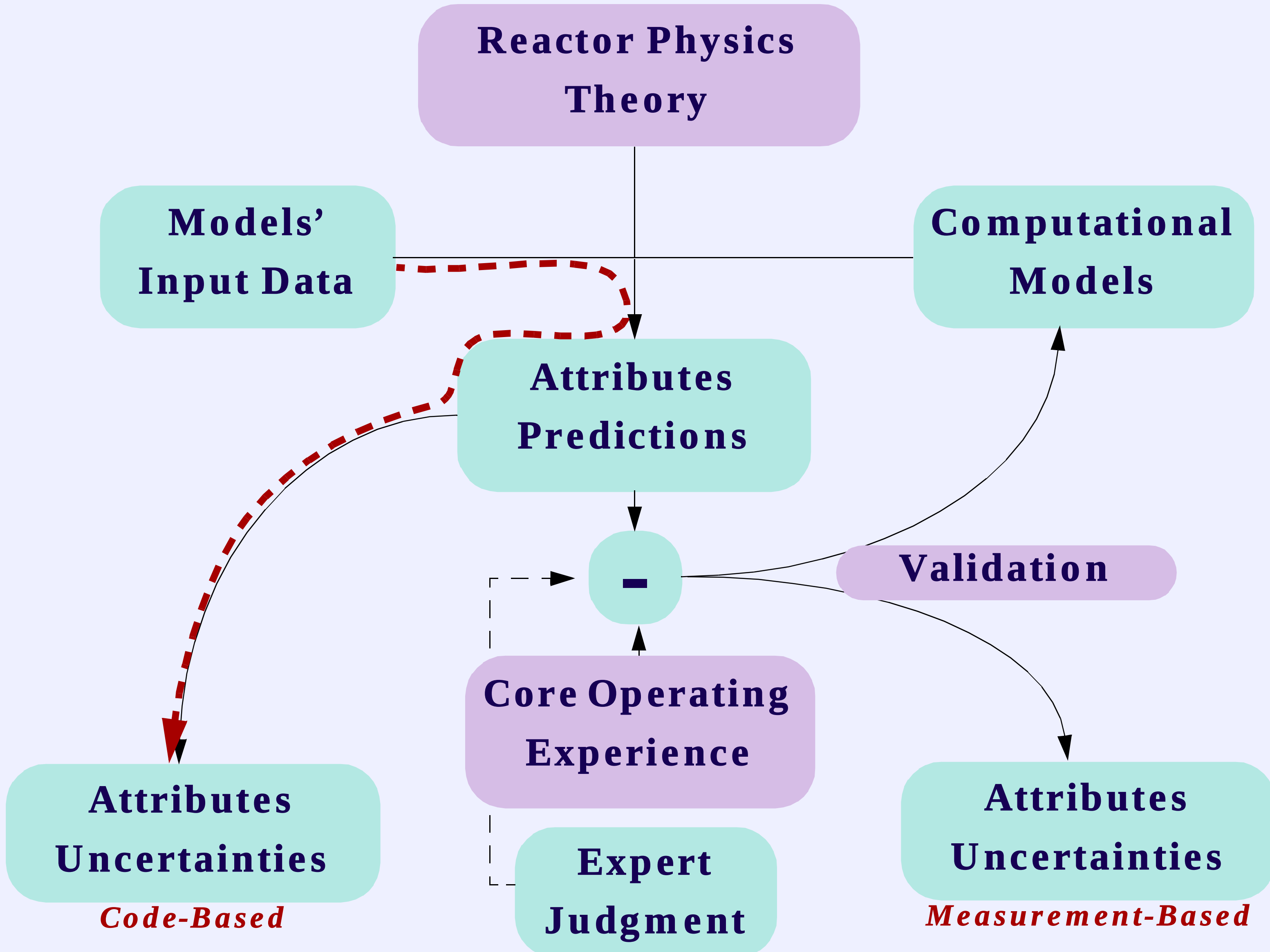
*Patent pending on ESM.

Possible Uncertainty & Sensitivity Analyses Approaches

- Modified Forward Approach [cont.]
  - Attributes
    - Simple to implement for uncorrelated and correlated input data
    - Well suited for problems with many key attributes and many input data
    - Does not provide probability distributions of key attributes [may be able to do this if random vectors generated using data uncertainty information]
    - Directly obtain sensitivity coefficients
    - Correlated input data treated without difficulty

Sample Application of Efficient Subspace Method

- Commercial BWR core application [completed previously as portion of adaptive core simulator research by former student Dr. Hany Abdel-Khalik]
- Wish to determine uncertainties of node-wise core power distribution and core reactivity as a function of cycle exposure, *i.e.* burnup. Needless to say, uncertainties in EOC discharged isotopic number densities were also determined.
- 10^6 input data and 10^5 key attributes.


Reactor Physics Theory
Models' Input Data
Computational Models
Attributes Predictions
-
Validation
Core Operating Experience
Expert Judgment
Attributes Uncertainties
Code-Based
Attributes Uncertainties
Measurement-Based

Uncertainty Propagation

- **Illustrative example:**
  - Propagate ENDF/B uncertainty information through lattice physics codes to important core attributes.

- **Other examples:**
  - Burnt fuel isotopic concentration uncertainties.
  - Repository performance metrics.
  - Thermal-hydraulic attributes.

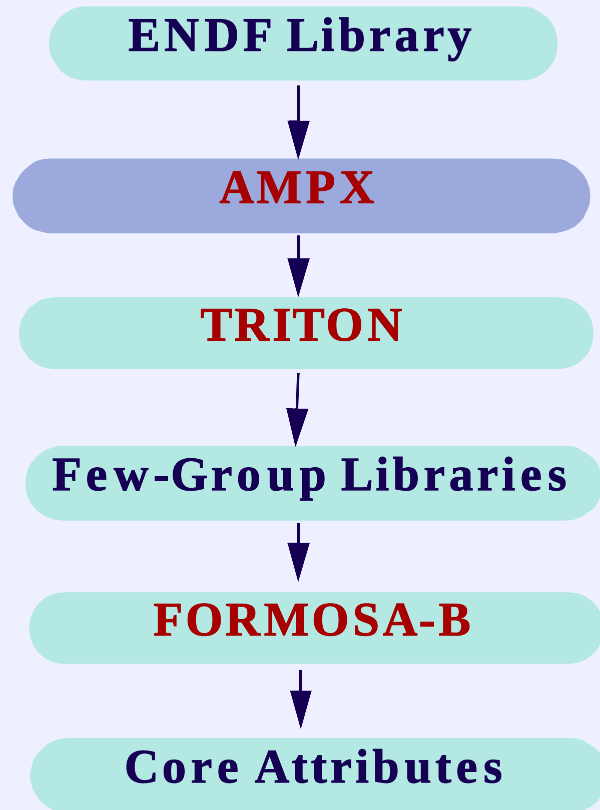
Case Study

- **AMPX-TRITON (ORNL) + FORMOSA-B (NCSU)**

- **AMPX: 44Group5Cov**

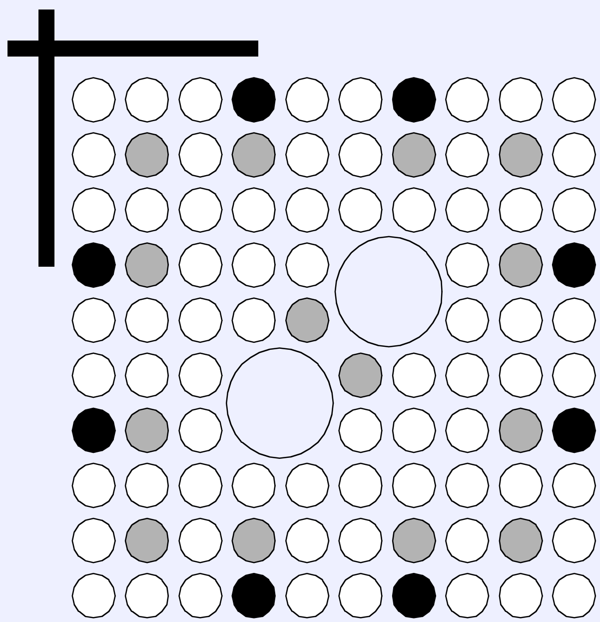
  - 29 different nuclides, e.g. Al-27, Am-241,B-10,C-12,U-235,U-238, Pu-239,Pu-240,Pu-241

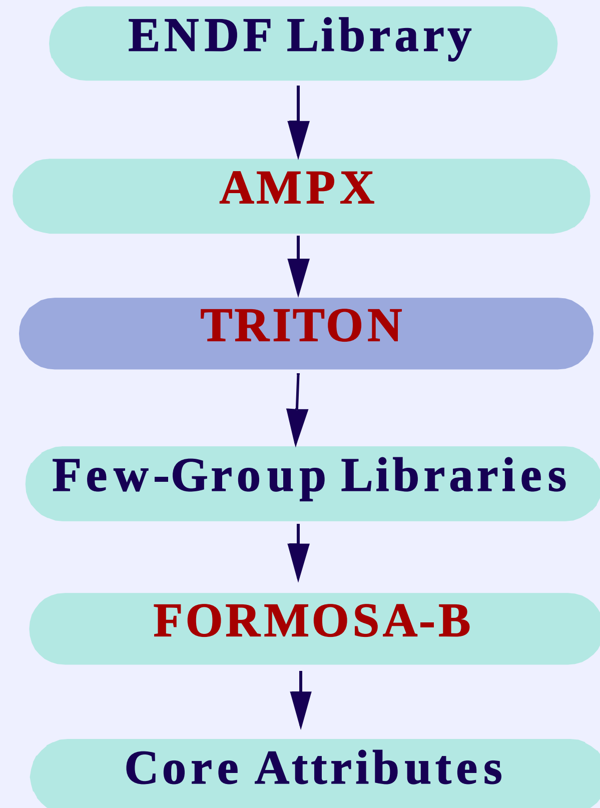
  - Missing important isotopics, e.g. Samarium, and Gadolinium. (Assumed to have zero uncertainty).



Case Study

- **AMPX-TRITON (ORNL) + FORMOSA-B (NCSU)**
- **GE-12, 10x10 lattice.**





Case Study

- **AMPX-TRITON (ORNL) + FORMOSA-B (NCSU)**

- **BWR/3 reload core**
  - Cycle Exposure ~ 20 GWD/MTU
  - Number of FAs = 560.

ENDF Library
↓
AMPX
↓
TRITON
↓
Few-Group Libraries
↓
FORMOSA-B
↓
Core Attributes

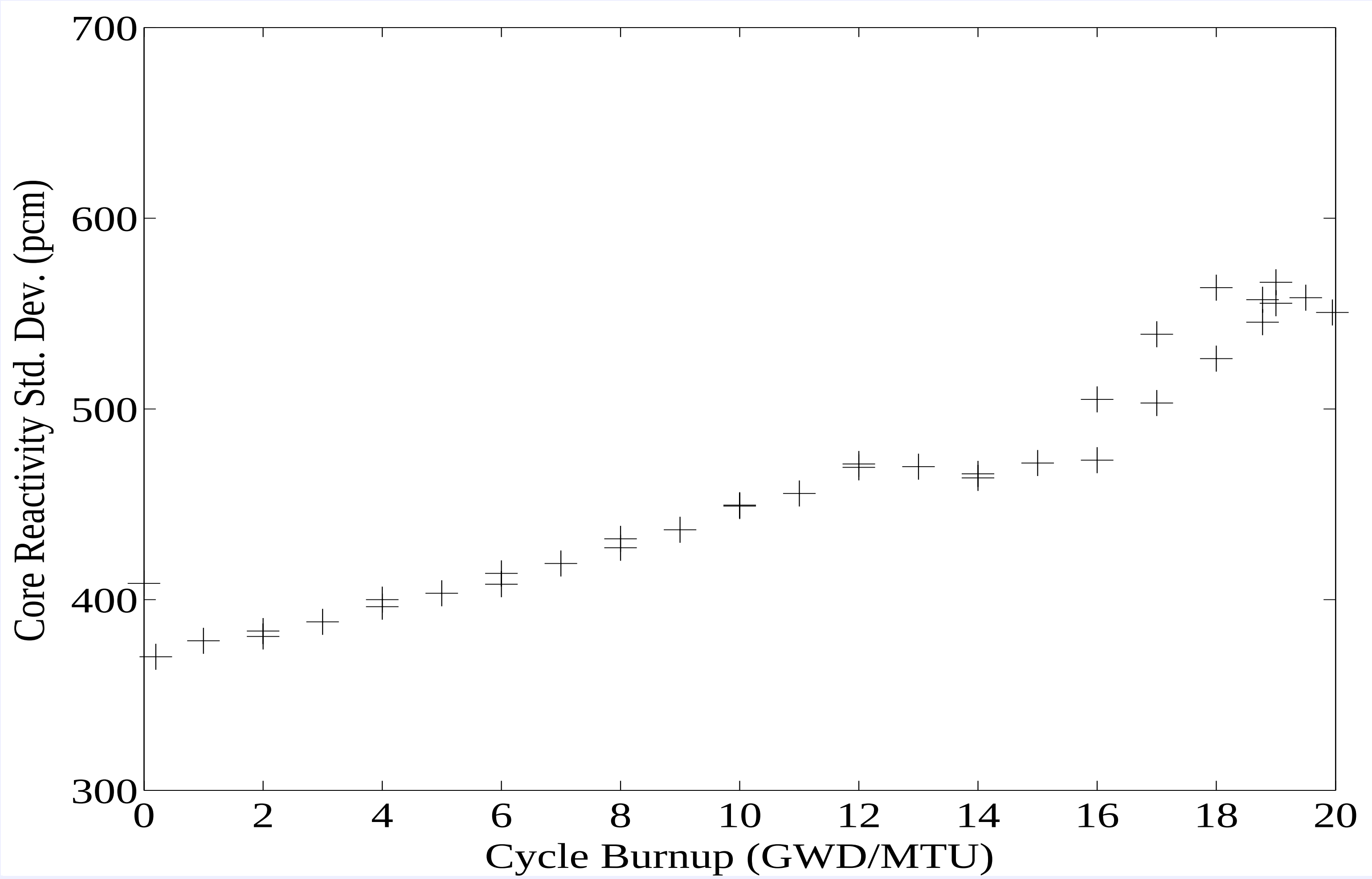
Case Study

- **AMPX-TRITON (ORNL) + FORMOSA-B (NCSU)**

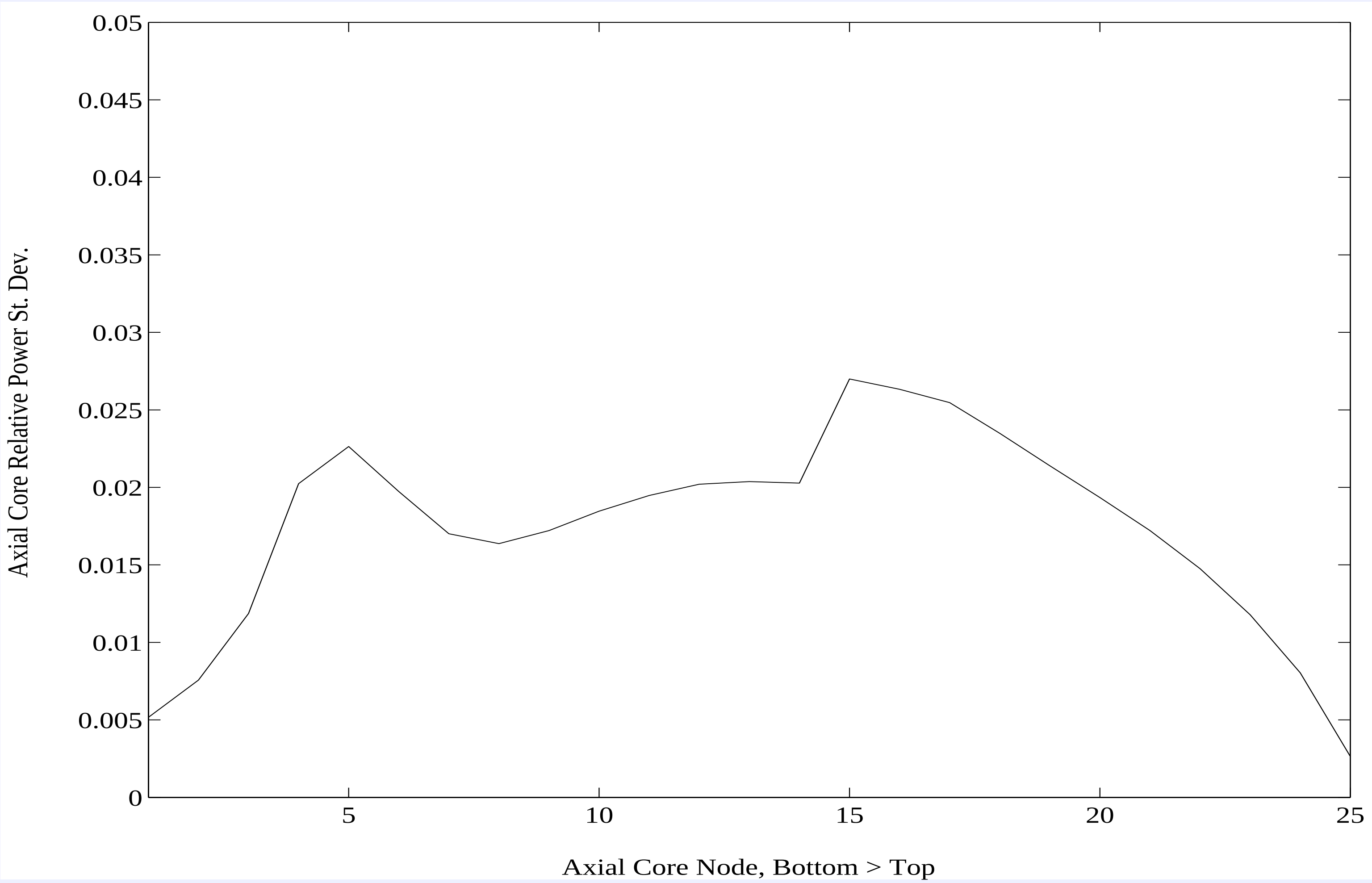
- **Core Attributes:**
  - **- Core critical eigenvalue.**
  - **- Core power distribution.**

ENDF Library → **AMPX** → **TRITON** → **Few-Group Libraries** → **FORMOSA-B** → **Core Attributes**

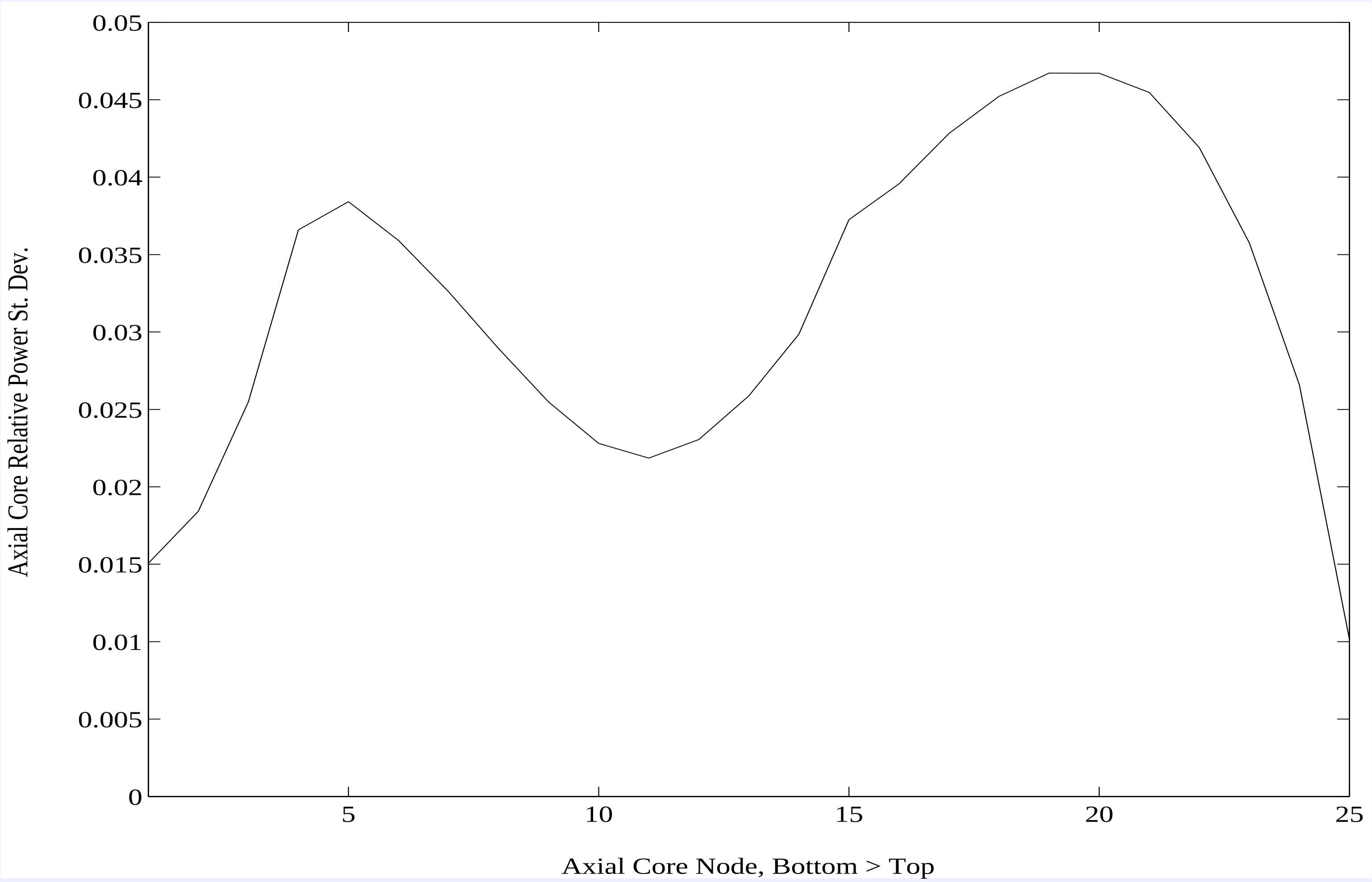
Core Reactivity Uncertainty



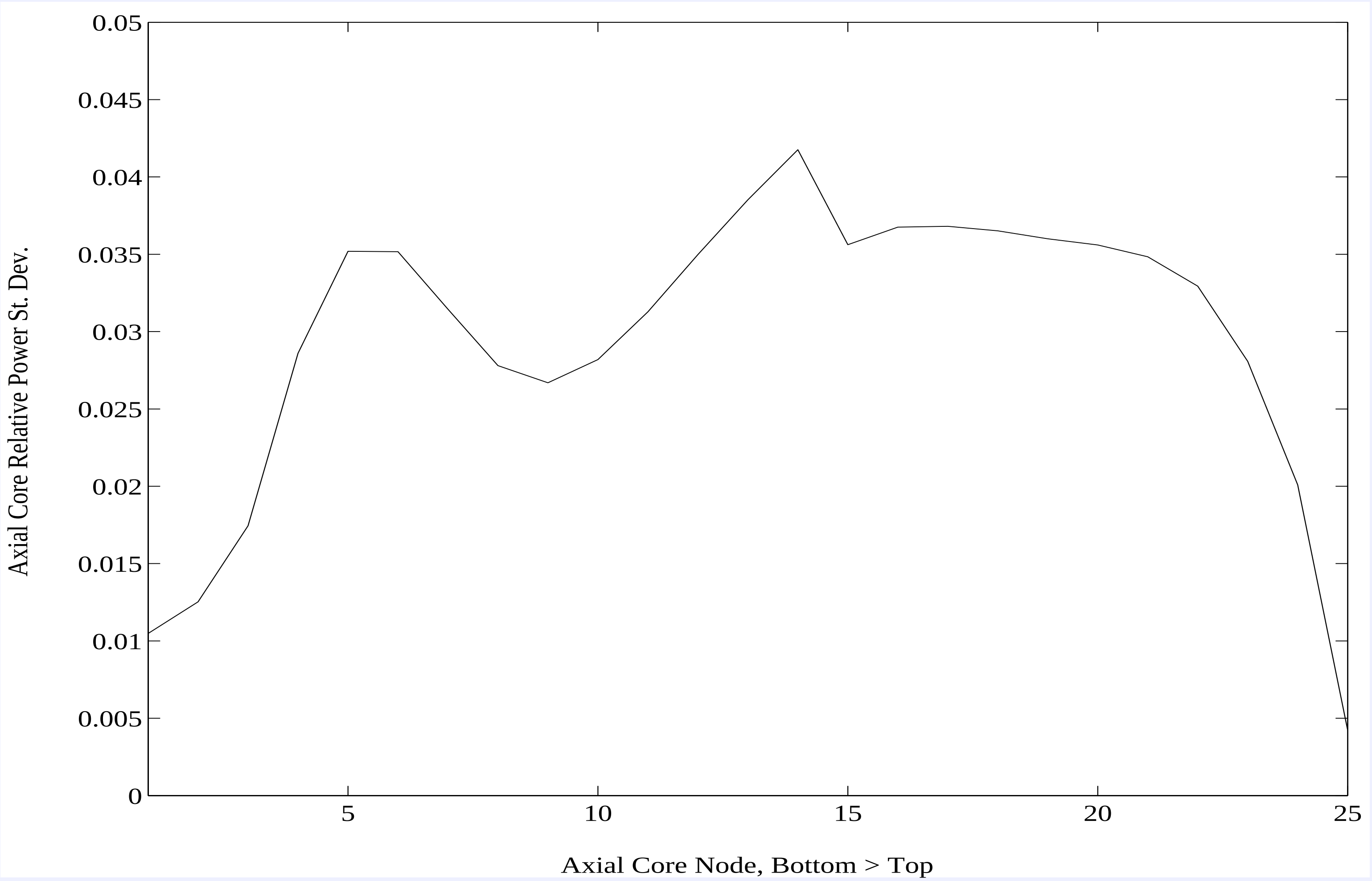
Core Axial Power Uncertainty (BOC)



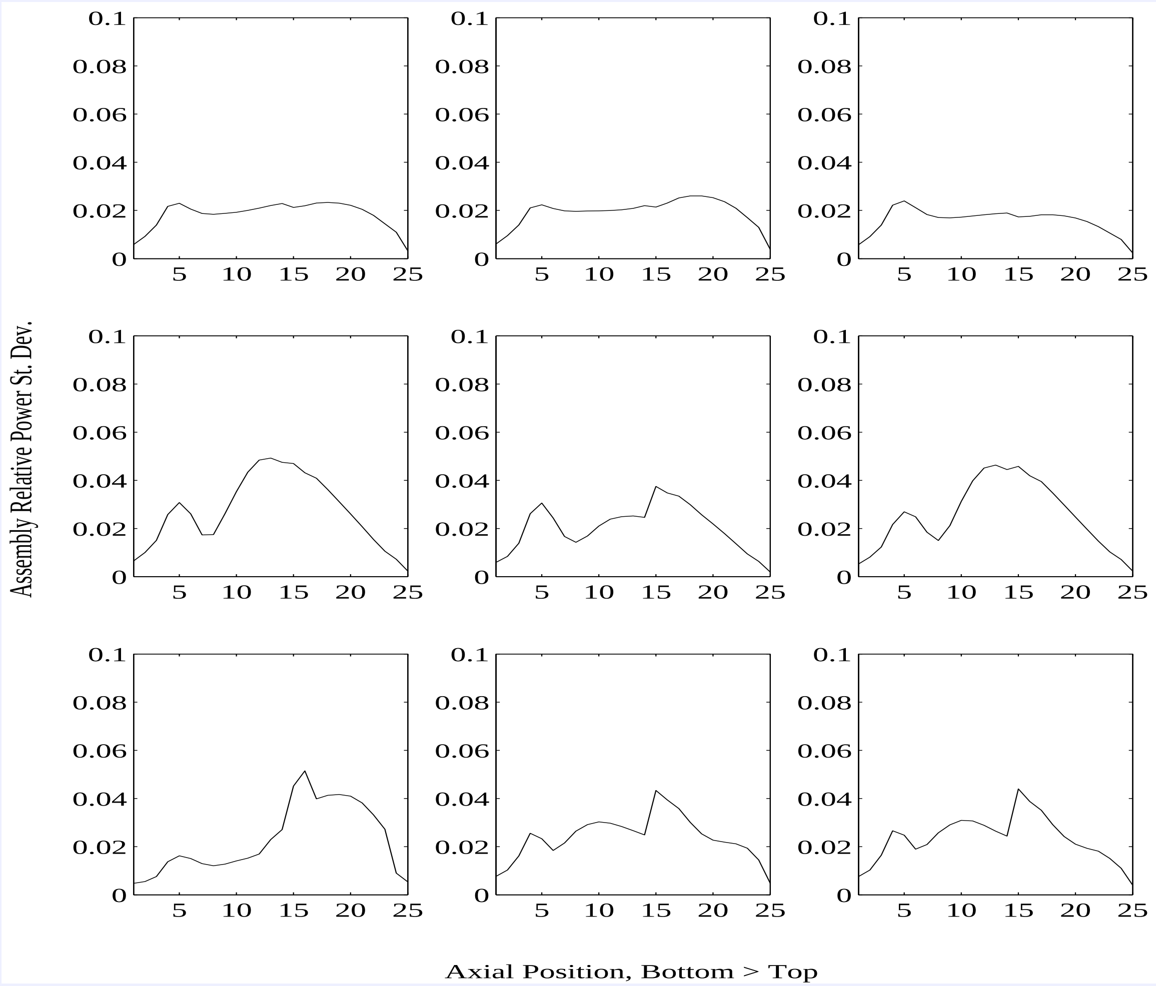
Core Axial Power Uncertainty (MOC)



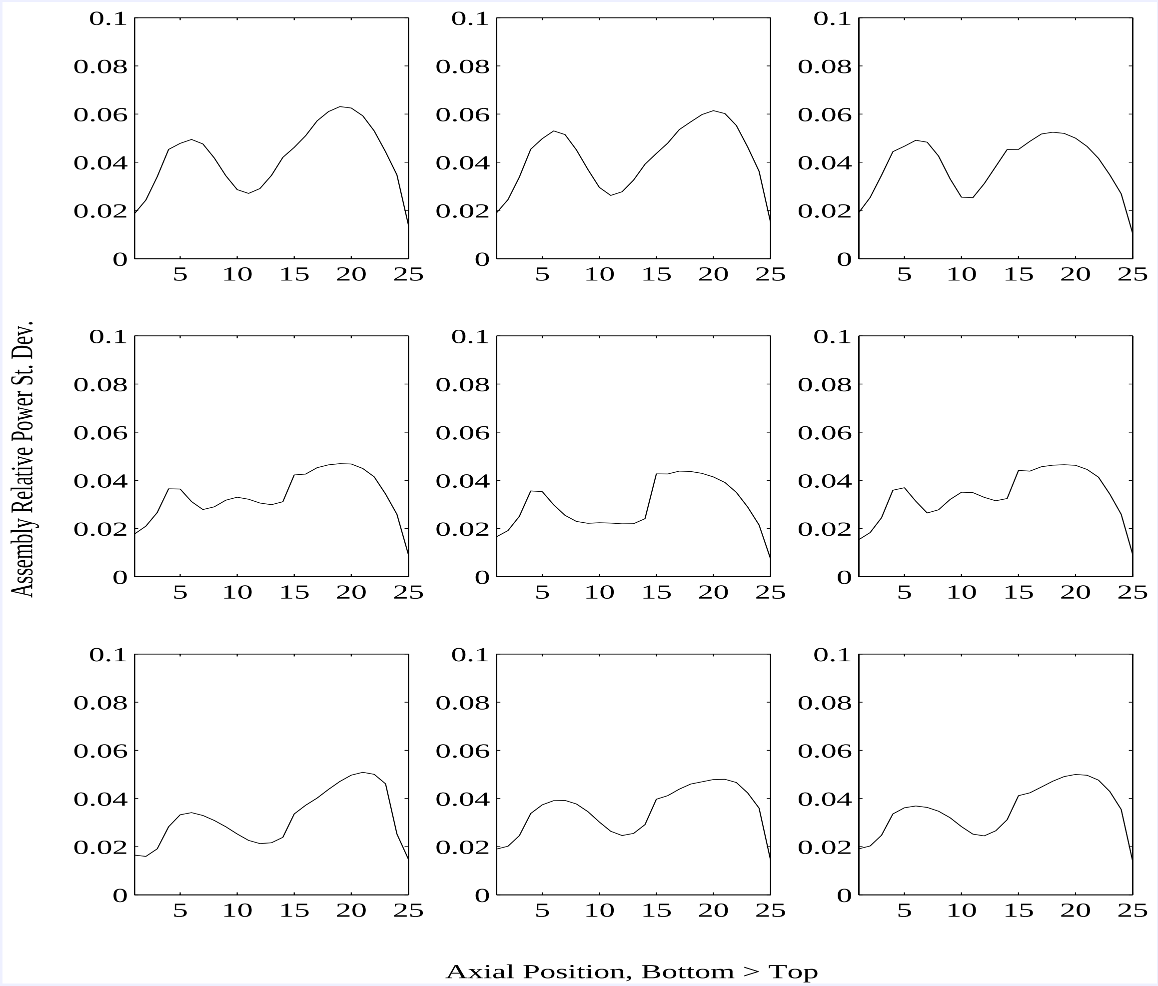
Core Axial Power Uncertainty (EOC)



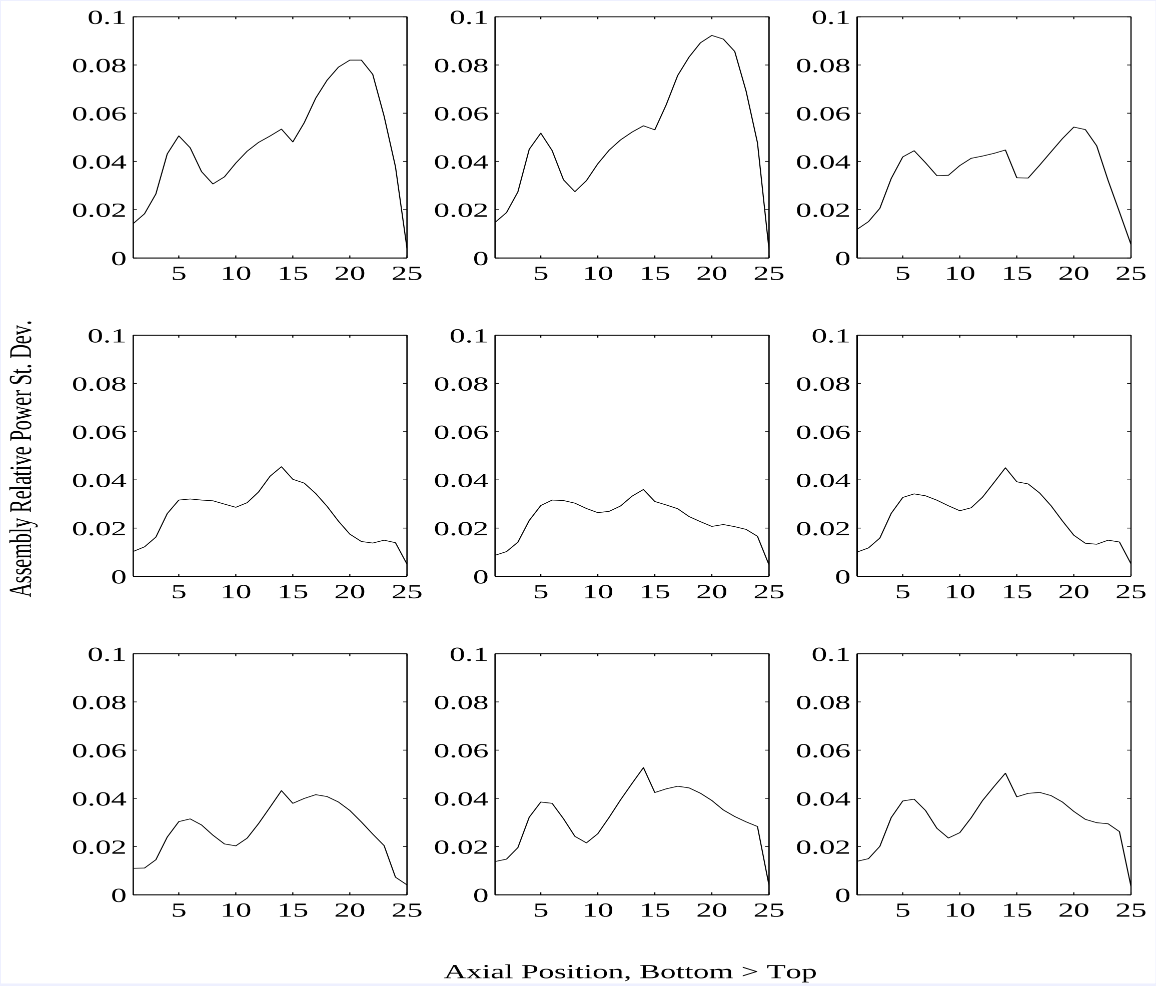
FA Axial Power Uncertainty (BOC)



FA Axial Power Uncertainty (MOC)



FA Axial Power Uncertainty (EOC)



Development Cycle Implications

1. All model development should consider how modeling uncertainties are going to be assessed.
2. Treating modeling and input data uncertainties needs to be considered early in development cycle.
3. Computational resources required to treat uncertainties can easily be one or two orders of magnitude higher than what the simulation model requires.
4. Experimental and/or benchmark evaluations of uncertainties in simulation models is a mandatory step in the development cycle.